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A Novel Adaptive Neuro Fuzzy Inference System Based Classification Model for Heart Disease Prediction

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ABSTRACT

Adaptive Neuro Fuzzy Inference System (ANFIS) is among the most efficient classification and prediction modelling techniques used to develop accurate relationship between input and output parameters in different processes. This paper reports the design and evaluation of the classification performances of two discrete Adaptive Neuro Fuzzy Inference System models, ANFIS Matlab's built-in model (ANFIS_LSGD) and a newly ANFIS model with Levenberg-Marquardt algorithm (ANFIS_LSLM). Major steps were performed, which included classification using grid partitioning method, the ANFIS trained with least square estimates and backpropagation gradient descent method, as well as the ANFIS trained with Levenberg-Marquardt algorithm using finite difference technique for computation of a Jacobian matrix. The proposed ANFIS_LSLM model predicts the degree of patient's heart disease with better, reliable and more accurate results. This is due to its new feature of index membership function that determines the unique membership functions in an ANFIS structure, which indexes them into a row-wise vector. In addition, an attempt was also done to specify the effectiveness of the model's performance measuring accuracy, sensitivity and specificity. A comparison of the two models in terms of training and testing with the Statlog-Cleveland Heart Disease dataset have also been done.

Keywords: Adaptive neuro fuzzy inference system, Classification, Grid Partitioning Method, Levenberg-Marquardt algorithm, Prediction

INTRODUCTION

Heart attack disease remains the main cause of death rate worldwide. The World Health Organisation estimated 17.5 million people died from cardiovascular diseases in 2012, representing 31% of all deaths around the globe. An estimate of 16 million deaths under the age of 70 were due to non-communicable diseases, 82% of which are in low- and middle-income countries. About 7.4 million were due to coronary heart disease, and 6.7 million were due to stroke (WHO, 2015).

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In order to investigate the misfortune of heart attack, certain factors that are associated with lifestyle need to be addressed. Therefore, people with heart disease due to the presence of chest pain, resting blood pressure, cholesterol, fasting blood sugar resting electrocardiographic and maximum heart rate need early detection and prediction for better counselling and appropriate medicine. Some factors make physicians' work even more difficult to be analysed by evaluating the existing test results of patients. As such, some complicated measures are not easy to perform when considering large number of factors. Anooj (2012) and Hedeshi and Abadeh (2014) stated that the decision about the presence or absence of a patient with certain diseases depends on the physician's intuition, experience and skill in comparing with the previous ones than on knowledge-rich data hidden in the database. This measure is a challenging task with regards to the large number of factors that has to be considered. In order to achieve our goals in this complex stage, the physician may need accurate and efficient hybrid fuzzy expert systems that can classify and predict the likelihood of a patient getting a heart disease problem and being able to help in diagnosing disease.

Classification is a process used to find a model that describes and differentiates data classes or concepts for the purpose of using the model to predict the class of objects whose class label is unknown.

Over a decade, the literatures about the use of intelligent methods in the medical sector had a vast number of related works (Muthukaruppan & Er, 2012; Sikchi et al., 2012; Kumar, 2013; Sikchi et al., 2013). The medical practitioners make use of computerised technologies to assist in diagnosis and give suggestions as medical diagnosis is full of uncertainty. According to Opeyemi and Justice (2012), the best and most efficient techniques for dealing with uncertainty is by incorporating fuzzy logic and neural network.

Fuzzy logic, which was conceived by Zadeh (1965), is a form of many valued logic in which a truth value of variables may be any real number between 0 and 1. In fuzzy logic, everything allows or is allowed to be a matter of degree, imprecise, linguistic and perception based. Fuzzy logic provides a foundation for the development of new tools for dealing with natural languages and knowledge representation. Its aim is at formalisation of reasoning modes which are approximate rather than exact. Fuzzy logic has four principal facets of logical, set theoretic, relational and epistemic (Zadeh, 2004).

There are diverse types of studies based on ANFIS methodologies (Palaniappan & Awang, 2008; Patil & Kumaraswamy, 2009; Abdullah et al., 2011; Zhu et al., 2012; Kar & Ghosh, 2014; Mayilvaganan & Rajeswari, 2014; Yang et al., 2014).

This research work involves developing a framework that incorporates hybrid learning algorithms least square estimates with gradient descent and Levenberg-Marquardt algorithm on the training Statlog-Cleveland Heart Disease Dataset.

The remaining part of this paper is organised as follows; in section 2, the designs of newly adaptive neuro-fuzzy models are presented. This led us to section 3, in which simulation results are described, while the discussion and conclusion part of the work is given in section 4.

METHODS AND MATERIALS

According to Nguyen et al. (2003), Takagi Sugeno Kang Fuzzy model's rules are given in the form of:

$$R_i\text{: if } x_i \text{ is } A_i \text{ then } f_i(x), i = 1,2,\dots,n \tag{1}$$

where

$$f_1, f_2, \dots, f_n \text{ are functions } X = X_1 * X_2 * \dots X_k \rightarrow R \text{ and } A_i = \bigwedge_{j=1}^{k} A_{ij} \tag{2}$$

These rules are combined to get a function:

$$R(x) = \frac{A_1(x)f_1(x) + A_2(x)f_2(x) + \cdots + A_n(x)f_n(x)}{A_1(x) + A_2(x) + \cdots + A_n(x)} \tag{3}$$

This TSK fuzzy model produces a real-valued function.

ANFIS was first introduced by Jang (1993). NFIS is a framework of adaptive techniques to assist learning and adaptation. To illustrate the ANFIS structure, two fuzzy IF-THEN rules according to a first order Sugeno model are to be considered for simplicity based on the following algorithms:

Layer 1: Calculate the Membership Functions values for inputs.

$$O_i^1 = \mu_{Ai}(x) = e^{-\frac{1}{2}\left(\frac{x-c_i}{\sigma_i}\right)}, i = 1,2 \tag{4}$$

$$O_i^1 = \mu_{Bi-2}(y) = e^{-\frac{1}{2}\left(\frac{y-m_i}{\beta_i}\right)}, i = 3,4 \tag{5}$$

Layer 2: Calculate the rule firing strengths.

$$O_i^2 = w_i = \mu_{Ai}(x) * \mu_{Bi}(y) = e^{-\frac{1}{2}\left(\frac{x-c_i}{\sigma_i}\right)} * e^{-\frac{1}{2}\left(\frac{y-m_i}{\beta_i}\right)}, i = 1,2 \tag{6}$$

Layer 3: Determine the normalised firing strengths

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} = \frac{\mu_{Ai}(x) * \mu_{Bi}(y)}{\mu_{Ai}(x) + \mu_{Bi}(y)}, i = 1,2 \tag{7}$$

Layer 4: Calculate the rules outputs for rule consequent layer

$$O_i^4 = \overline{w}_i f_i = w_i(p_i x + q_i y + r_i), i = 1,2 \tag{8}$$

Layer 5: Calculate the overall output

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, i = 1,2 \tag{9}$$

Image of the ANFIS Structure

Figure 1 shows the structure of Adaptive Neuro Fuzzy Inference System (ANFIS), as described in equations (4) – (9). The structure of the proposed model contains five layers, input and output layers, and three hidden layers that represent membership functions and fuzzy rules.

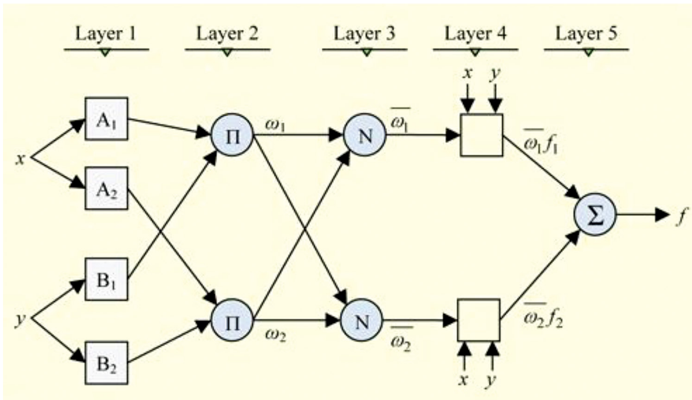

Figure 1. The ANFIS structure

Rules Index Vector

Index Membership function is the index vector that keeps track of the unique MFs. This function determines the unique MFs in the ANFIS structure and indexes them row-wise. In case two rules use the same MF, then their indices will be the same (rows are the rules, columns are the inputs). For Inputs, rule list is a Nr * Ni matrix that identifies the membership functions for the ith rule & jth input, and for outputs that include index MF, which is the index table of the unique MF used in the rules, while Nf is the number of unique MFs. Where Nr = Number of Rules and Ni = Number of Inputs. Therefore, the final index vector collects the indices found in MF "row-wise" according to the rules.

We consider a rule list of:

$R = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 & 2 & 2 & 2 \end{bmatrix}$, and [3, 4, 3, 4, 2, 3, 3] the number of membership function for each input, respectively.

HYBRID LEARNING ALGORITHM OF ANFIS

The main idea of the learning algorithm is to adjust all of the modifiable parameters such as $[a_i, b_i, c_i]$ and $[p_i, q_i, r_i]$ for the purpose of matching the ANFIS output with the training data. There are two passes for hybrid algorithm, forward pass and backward pass. In the forward pass of hybrid algorithm, when the values of premise algorithm are fixed, the overall output can be expressed as a linear combination of the consequent parameters by Ziasabounchi and Askerzade (2014). For unchanging the parameters of the membership function, the output of the ANFIS model can be written as:

$$\mathrm{F} = \sum_{\mathrm{i}} \bar{\mathrm{w}}_{\mathrm{i}}\, \mathrm{f}_{\mathrm{i}} = \frac{\sum_{\mathrm{i}} \mathrm{w}_{\mathrm{i}} \mathrm{f}_{\mathrm{i}}}{\sum_{\mathrm{i}} \mathrm{w}_{\mathrm{i}}}, \mathrm{i} = 1,2$$

$$= (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2 \quad (10)$$

From (10), the parameters $\mathrm{p_i},\ \mathrm{q_i}\ \&\ \mathrm{r_i}$ are to be updated by a least square estimate using Moore-Penrose pseudo-inverse, which incorporates SVD decomposition for robustness that minimises the errors $||AX - B||^2$ by approximating X with X*.

A = Output produced by O_i^3, B = Target output, X = Unknown consequent values related to the set of consequent parameters $p_i,\ q_i\ \&\ r_i$.

$$X^* = (\mathrm{A^T A})^{-1}\mathrm{A^T B} \quad (11)$$

The ANFIS Models Design

Adaptive Neuro Fuzzy Inference System is one of the hybrid neuro fuzzy inference expert systems that has the potential to capture the benefits of both artificial neural network learning rules to conclude and adjust the fuzzy inference systems, particularly in Takagi Sugeno Kang type fuzzy inference system. Grid Partition method was used to create initial membership functions. At the very beginning of the training, this method divides the data space into rectangular sub-spaces using axis-paralleled partition based on a predefined number of membership functions and their types in each dimension (Wei et al., 2007).

Grid Partition method generates rules by enumerating all possible combinations of the membership functions of all inputs. Most of the researchers used less input variables (less than 5) in grid partitioning method. In our case, we used Gaussian membership functions for each of the input variables. The number of these membership functions is shown in Table 1. Seven inputs with these membership functions result in 2,592 fuzzy if-then rules. In these proposed ANFIS models (ANFIS_LSGD and ANFIS_LSLM), we set the initial learning rate, mu = 1e-1, h = 1e-8 and number of epoch = 1800.

The Proposed ANFIS_LSGD Model Design

In designing this model, a hybrid learning technique based on the ANFIS Matlab's built-in model using Least squares estimate and backpropagation gradient descent training algorithm is used.

Forward Pass

Least squares estimate (LSE) is used at the very beginning to get the initial values of the conclusion parameters, and then at backward pass for the gradient descent take over to update all parameters. When the values of the premise parameters are fixed, the overall output can be expressed as in (10), which is linear in the consequent parameters.

Let

$$B = AX \tag{12}$$

If X is invertible matrix then

$$X = A^{-1}B \tag{13}$$

$$X^{*} = (A^{T}A)^{-1}A^{T}B \tag{14}$$

Otherwise a pseuso-inverse is used to solve for X

Backward Pass

The error signal propagate backward and premise parameters are updated by gradient descent,

$$\alpha_{ij}(t+1) = \alpha_{ij}(t) - \eta . \frac{\partial E}{\partial \alpha} \tag{15}$$

where η is the learning rate for α_{ij}, which can be further expressed as:

$$\eta = \frac{k}{\sqrt{\sum_{\alpha}\left(\frac{\partial E}{\partial \alpha}\right)^{2}}} \tag{16}$$

where k is the step size, the length of each gradient transition in the parameter space.

The chain rule is used to calculate the partial derivatives to update the membership function parameters:

$$\frac{\partial E}{\partial \alpha_{ij}} = \frac{\partial E}{\partial f} . \frac{\partial f}{\partial f_i} . \frac{\partial f_i}{\partial w_i} . \frac{\partial w_i}{\partial \mu_{ij}} . \frac{\partial \mu_{ij}}{\partial \mu_{ij}} \tag{17}$$

The Proposed ANFIS_LSLM Model Design

In designing this new ANFIS model, a hybrid learning technique based on Least squares estimate and Levenberg-Marquardt algorithm with finite difference method for computing the Jacobian Matrix was used.

Forward Pass

Least squares estimate (LSE) was used at the very beginning to get the initial values of the conclusion parameters, and then at backward pass for the Levenberg-Marquardt algorithm take over to update all the parameters. When the values of the premise parameters are fixed, the overall output can be expressed as in (10), followed by (11) – (14).

Backward Pass

For the Levenberg-Marquardt algorithm, the performance index to be optimised is defined as:

$$\mathrm{F(w)} = \frac{1}{2}\mathrm{E^T E} \tag{18}$$

Error signals are propagated and the premise parameters are to be updated by the Levenberg-Marquardt algorithm:

$$\mathbf{W}_\mathrm{k}(\mathrm{t}+1) = \mathbf{W}_\mathrm{k} - \left(\mathrm{J_k^T J_k} + \mu\mathrm{I}\right)^{-1}\mathrm{J_k^T E(w)} \tag{19}$$

$$\Delta\mathbf{W}_\mathrm{k} = (\mathrm{J_k} + \mu\mathrm{I})^{-1}\mathrm{J_k^T E(w)} \tag{20}$$

Get the parameters of unique MF_s of current FIS as presented in rules index vector; and Obtain Cumulative Current Error vector and RMSE

$$\mathrm{E(w)} = [\mathrm{e_{11}} \dots \mathrm{e_{k1}}\ \mathrm{e_{12}} \dots \mathrm{e_{k2}} \dots \mathrm{e_{kp}}]^\mathrm{T} \tag{21}$$

where $\mathrm{e_{kp}} = \mathrm{d_{kp}} - \mathrm{o_{kp}},\ \mathrm{k} = 1,2, \dots, \mathrm{K},\ \mathrm{p} = 1, \dots, \mathrm{P}$

$$\mathrm{rmse1} = \sqrt{\frac{\mathrm{E_p}}{\mathrm{p}}} \tag{22}$$

Built up Jacobian matrix column–wise, which contains 1st order partial derivatives of network error using the central difference method

$$\mathrm{f}'(\mathrm{x_0}) = \frac{\mathrm{f_1} - \mathrm{f_{-1}}}{2\mathrm{h}} + \mathrm{E_{trunc}}(\mathrm{f}, \mathrm{h}), \tag{23}$$

where $\mathrm{f_1} = \mathrm{f(x+h)}$

Therefore,

$$\mathrm{J_{i,j}} = \frac{\partial \mathrm{f_i}}{\partial \mathrm{x_j}} \tag{24}$$

Transform Jacobian into sparse matrix to speed things up

$$\mathrm{J_{i,j}} = \mathrm{Sparse}\left(\frac{\partial \mathrm{f_i}}{\partial \mathrm{x_j}}\right) \tag{25}$$

Approximate Hessian matrix, which contains 2nd order partial derivative of network error using the cross product of Jacobian.

$$\mathrm{H} \approx \mathrm{J^T J} \tag{26}$$

Therefore,

$$H_{i,j} = \frac{\partial^2 f_i}{\partial x_i \partial x_j} \tag{27}$$

Compute the error gradient

$$g = J^T E \tag{28}$$

Update the Hessian matrix

$$H^* = [H + \psi I] \tag{29}$$

where I is the sparse identity matrix and $\psi = 0.1$ is the learning parameter; and the network parameter needs to be updated using (20).
Recalculate the RMSE using the updated parameters,

$$rmse2 = \sqrt{\frac{E_p}{p}} \tag{30}$$

Adjust the learning parameters; if total error is decreased as a result of the update, then go to the next epoch; otherwise, if total error is increased, then increase learning rate. Finally, if rmse2 is less than rmse1, accept; otherwise reject.

Description of Input attributes

The dataset is available from the University of Strathclyde, Glasgow, Scotland, U.K., via Ross (1992). Detailed information about the input variables is shown in Table 1.

Table 1
Information about input variables

Variable Name	Min	Max	No. of MF	Description of Input Variable	Type
AGE	29	77	3	Age (very young, young & old)	Real
CP	1	4	4	Chest pain type (1-typical angina, 2- atypical angina, 3- non-anginal pain, 4-asymtomatic)	Nominal
TRESTBPS	94	200	3	Resting blood pressure (Low, Normal & High)	Real
CHOL	126	564	3	Cholesterol (low, medium, high & very high)	Real
FBS	0	1	2	Resting blood sugar (0=false, 1=true) it is true when fbs>120	Binary
RESTECG	0	2	3	Resting electrocardiographic (0-normal, 1-having ST-T & 2-showing definite left VH)	Nominal
THALACH	71	202	2	Maximum heart rate (low, normal & high)	Real

Accuracy, Sensitivity and Specificity

To be confidently used in medical decision-making, the test methods must meet tough standards of statistical measurements: sensitivity, specificity and accuracy, which are the terms most commonly associated with the Binary classification test and they statistically measure the performance of the test by Saed (2015).

RESULTS AND DISCUSSION

In this research work, an attempt was made to develop and examine the ability of two ANFIS models for predicting heart disease.

Performance Evaluation

After training the system, it has to be tested with a set of testing dataset so as to verify the capacity of the models. This determines how well the ANFIS models are worked. Accuracy was calculated based on the correct classified instances divided by the total number of instances (Patil et al., 2010).

System Validation

Validation is the process of determining the degree to which a model is an accurate real world representation from the perspective of the intended uses of the model (Thacker et al., 2004). Therefore, to measure the stability of performance, the data are divided into training and testing using the validation method. Hold-out validation method is used for testing of results.

Hold-out Validation Method

The data were split into two groups, namely, training set and test set. The total number of samples used was 270, out of which the first 180 were for training and the remaining 90 for testing.

Results of Accuracy, Sensitivity and Specificity

The measure of the ability of the classifier to produce accurate diagnosis is determined by accuracy. The measure of the ability of the model to identify the occurrence of a target class accurately is determined by sensitivity. The measure of the ability of the model to separate the target class is determined by specificity (Kahramanli, 2008).

Classification results of the correct and incorrect number of predicted values, as well as the performance of our results of accuracy are shown in Table 4 and Table 5, respectively.

Table 2
Obtained Statlog-Cleveland Heart Disease classification results

	ANFIS_LSGD	ANFIS_LSLM
Train-correct predicted value	135	135
Train-incorrect predicted value	45	45
Test-correct predicted value	68	69
Test-incorrect predicted value	22	21

Table 3
Accuracy Results of the proposed models

	ANFIS_LSGD		ANFIS_LSLM	
	Train (%)	Test (%)	Train (%)	Test (%)
Sensitivity	68.29	71.05	68.29	71.05
Specificity	80.61	78.85	80.61	80.77
F-measure	71.34	71.05	71.34	72.00
Precision	74.67	71.05	74.67	72.97
Accuracy	75.00	75.56	75.00	76.67

Root Mean Square Error (RMSE)

Root Mean Square Error is one of the most acceptable indicators that describes the differences between the actual data and the predicted values. The values of the premise and consequent parameters can be obtained after network training by directly minimising the RMSE performance criterion (Ho et al., 2009).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y - y')^2} \tag{31}$$

where y and y' are ith desired output and predicted output respectively; and N is the number of total points.

Table 4
The values of RMSE

	ANFIS_LSGD	ANFIS_LSLM
RMSE	0.40344	0.40327

Comparison of the Results

According to Kathy (2013), the train or test error rates can be obtained as the ratio of number of incorrect predicted values to the total number of train or test instances.

Table 5
A comparison of the results with other algorithms based on error rates (train & test) (Michie et al., 1994).

Algorithm	Error (Train)	Error (Test)	Reference
Proposed (ANFIS_LSLM)	**0.25**	**0.233**	**This study**
Proposed (ANFIS_LSGD)	**0.25**	**0.244**	**This study**
k-NN,k=30,eucl,std	-	0.344	KG
NaiveBay	0.351	0.374	Statlog
Discrim	0.315	0.393	Statlog
Logdisc	0.271	0.396	Statlog
ALLOC80	0.394	0.407	Statlog
Quadisc	0.274	0.422	Statlog
CASTLE	0.374	0.441	Statlog
Cal5	0.330	0.444	Statlog
CART	0.463	0.452	Statlog
Cascade	0.207	0.467	Statlog
k-NN	0.000	0.478	Statlog
SMART	0.264	0.478	Statlog
DIPOL92	0.429	0.507	Statlog
ITrule	*	0.515	Statlog
Baytree	0.111	0.526	Statlog
Default	0.560	0.560	Statlog
Backprop	0.381	0.574	Statlog
LVQ	0.140	0.600	Statlog
IndCART	0.261	0.630	Statlog
Kohonen	0.429	0.693	Statlog
AC2	0.000	0.744	Statlog
CN2	0.206	0.767	Statlog
RBF	0.303	0.781	Statlog
C4.5	0.439	0.781	Statlog
NewID	0.000	0.844	Statlog
k-NN, k = 1, eucl, std	-	0.725	KG

Table 6
A comparison of the results with other classifiers for the Statlog-Cleveland Heart Disease (Department of Informatics, n.d.)

Method	Accuracy %	Reference
ANFIS_LSLM	**76.7**	**This study**
ANFIS_LSGD	**75.6**	**This study**
IR	71.4	WEKA, RA
T2	68.1	WEKA, RA
FOIL	64.0	WEKA, RA
RBF	60.0	ToolDiag, RA
InductH	58.5	WEKA, RA

Discussion of the Results

The number of correct and incorrect predicted values of the two classifiers is presented in Table 2. Both of the two classifiers predicted 135 and 45 as correct and incorrect values for the training dataset. For the test dataset, the two classifiers, ANFIS_LSGD and ANFIS_LSLM, classified the predicted values 68 & 22, and 69 & 21 as the correct and incorrect values, respectively.

The present research work further evaluates the performance of the proposed models using the Statlog-Cleveland benchmark dataset for Heart Disease prediction. The results showed that the performance measures were more important for interpreting the result of a classifier. The test performance of the classifiers was determined by the computation of sensitivity, specificity and total classification accuracy. As shown in Tables 3 and 4, the ANFIS_LSLM classifier yields better results when compared with the ANFIS_LSGD classifier.

Generally, the results of ANFIS_LSLM outperform the traditional ANFIS_LSGD even though the computational time for generating the ANFIS_LSGD was slightly faster when compared with ANFIS_LSLM. This is due to the complexity of computation of Jacobian matrix for each iteration, but it still yields better accuracy, which can be considered as efficient.

For the purpose of comparing with other algorithms, the results are shown in Table 5. Our proposed algorithms are found to be better than the accuracies of other algorithms in the literature for the Statlog-Cleveland heart disease dataset. From the previous research work and Table 6, it is clearly confirmed that none of the research studies has success rates higher than 71.4% for the mentioned algorithms on the Statlog-Cleveland Heart Disease Dataset. Based on the comparison of the results, it can be seen that the proposed models produced reasonable results in classifying the possible heart disease patients.

CONCLUSION

The objective of this study was to design two different ANFIS based classification models for heart disease prediction. It was observed that the classifiers learnt how to classify the dataset. Their performances were evaluated based on training, testing and accuracy of classification. We further conclude that this research work has so many features. We used grid partition technique, seven input variables with Gaussian membership functions resulting in 2,592 rules and achieved an accuracy of about 70% - 80% level. The root mean square error with the LS+LM and LM+GD algorithms after 1,800 iterations was found to be 0.40327 and 0.40344, respectively. The programme automatically compares the Matlab's built-in training to the Levenberg-Marquardt training and displays the results in a table format. The total classification accuracies obtained were 76.67% and 75.56% for the ANFIS_LSLM and ANFIS_LSGD classifiers, respectively.

The Levenberg-Marquardt algorithm has the problem of computational complexity of Jacobian matrix J at each iteration step by taking first order partial derivative and the inversion of J^TJ square matrix, the dimension of which is NxN. In the present work, the Jacobi is computed via central difference, which is made for a faster convergence speed by using sparse structure.

The results belong to the first attempt of study and confirmed that our proposed models were better than other models in the literature as they have the potential for classifying and predicting heart diseases. We thought if we adapted another means of computation of Jacobian matrix, the results would be improved for ANFIS_LSLM.

FUTURE WORK

The proposed ANFIS models could be enhanced in the future by:

1. Applying another means of derivation in computation of Jacobian matrix in order to increase convergence speed of the results.
2. Adapting another training algorithm such as Scaled Conjugate Gradient algorithm to produce better results.

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